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Solar geoengineering, uncertainty, and the price of carbon ☆

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ABSTRACT

We consider the socially optimal use of solar geoengineering to manage climate change and its implications for carbon emissions abatement policy. We show that solar geoengineering is a substitute for emissions abatement; optimal policy includes less abatement, by up to eight percentage points, and has a lower carbon price, by up to fifteen percent, than recommended by models that ignore solar geoengineering. However, it is an imperfect substitute, since it reduces temperature without reducing atmospheric or ocean carbon concentrations. Carbon concentrations are higher but temperature is lower when allowing for solar geoengineering. Ignoring geoengineering in climate models can lead to welfare losses of up to 4 percent of GDP. Uncertainty over climate sensitivity leads to more abatement and solar geoengineering, while uncertainty over solar geoengineering damages leads to less geoengineering.

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Introduction

Greenhouse gases (GHGs) like carbon dioxide contribute to climate change and thus create negative externalities. The standard Pigouvian solution to the market failure caused by negative externalities is to price the externality at marginal external damages. Solar geoengineering (SGE) is an alternative way to reduce the damages from GHGs: instead of reducing the quantity of GHGs, SGE can, at least in part, reduce the damages that they inflict by directly reducing incoming solar radiation. SGE does not, however, reduce atmospheric or ocean carbon concentrations. Furthermore, there is tremendous uncertainty over the risks of SGE. If SGE is part of the optimal policy portfolio, then its inclusion will affect the optimal amount of emissions reductions (abatement) and the optimal Pigouvian carbon price. Uncertainty over SGE risks and over the climate system itself may substantially affect optimal policies.

The purpose of this paper is to model how the possibility of SGE affects optimal climate policy, with a focus on the implications of uncertainty. Does ignoring SGE lead to policies that encourage too much abatement at too high a cost? How does uncertainty over climate change and over SGE damages affect optimal policy? How important is the fact that SGE reduces temperature but does not reduce carbon concentrations? To answer these questions, we add the possibility of a specific type of SGE to the Dynamic Integrated Climate-Economy (DICE) model (Nordhaus, 2014). We allow for uncertainty

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over both the effect of carbon on temperature and about the side effects of SGE. The model distinguishes between climate damages from temperature (which SGE can reduce) and climate damages from carbon concentrations (which SGE cannot). Costs and benefits of SGE are calibrated from various prior studies, and we conduct extensive sensitivity analyses. We calculate the welfare effects of introducing SGE. We caution that the purpose of this paper is not to argue one way or the other about the merits of SGE or to estimate the optimal level of its deployment, but rather point that ignoring SGE in models may lead to biased and incomplete policy recommendations.

Solar geoengineering (also called albedo modification or solar radiation management) is defined as the large-scale manipulation of the albedo, or reflectivity, of the planet to compensate for the greenhouse effect.[1] A small but growing literature examines the economics of solar geoengineering. One branch of that literature focuses on governance. Barrett (2014) summarizes this branch of the literature and calls governance "the fundamental problem posed by geoengineering."[2]

A second branch of the literature, which is smaller though perhaps more fundamental, focuses on the optimal use of SGE. Moreno-Cruz and Keith (2013) incorporate SGE into a two-period model of climate change and solve for optimal policy. They find that the uncertainty related to SGE is an important determinant of optimal policy. Including SGE can reduce the overall costs of climate policy by around 2 percentage points of GDP. Other papers have added SGE to integrated assessment models (IAMs) and examined the policy implications. Bickel and Lane (2009) show that SGE promises potentially large net benefits, though there is substantial uncertainty. They conduct a benefit-cost analysis of various levels of implementation of SGE, and they consider how implementing SGE affects carbon taxes. But, they do not solve for an optimal level of SGE. Goes et al. (2011) make several modifications to the DICE model and impose an exogenous intermittency in SGE which makes it less effective.[3] They present summaries of policies with an optimal mix of abatement and SGE (subject to the intermittency), but they do not present implications for policy, e.g. carbon taxes with SGE. Bickel and Agrawal (2013) extend the analysis of Goes et al. (2011) by considering alternate conditions under which SGE would be deployed; in contrast to Goes et al. (2011), Bickel and Agrawal (2013) find that under some scenarios a substitution of SGE for abatement can pass a cost-benefit test. Gramstad and Tjøtta (2010) include SGE in DICE and conduct a cost-benefit analysis of SGE under various assumptions about the level undertaken and its costs. Under all specifications, SGE passes a cost-benefit analysis, with net benefits ranging from $1.5 trillion to $17.8 trillion. They do not consider carbon taxes or the optimal level of SGE. [4]

Our paper falls under this second branch of the literature that examines optimal SGE policy. Our main contribution to the existing literature is our paper's focus on uncertainty. There are substantial uncertainties about the costs, benefits, and risks of SGE given the present state of scientific understanding. There is also uncertainty in our understanding of the climate, in particular over the equilibrium climate sensitivity, which measures how much temperature changes after doubling carbon dioxide (CO_2) concentrations from pre-industrial levels. We use a non-deterministic version of DICE to dynamically model uncertainty in solar geoengineering and in the climate system.[5] None of the other papers mentioned above that incorporate SGE into IAMs model uncertainty to the extent that we do. Bickel and Lane (2009) and Gramstad and Tjøtta (2010) do not model uncertainty. Goes et al. (2011) and Bickel and Agrawal (2013) conduct Monte-Carlo sensitivity analyses based on uncertainties over three parameter values: climate sensitivity, climate damages, and abatement costs. But, they do not consider uncertainty over any parameters related to geoengineering. Moreno-Cruz and Keith (2013) model uncertainty over SGE damages without using an integrated assessment model. Their treatment of uncertainty is limited to a two-point support distribution about future climate outcomes and the effectiveness of solar geoengineering. Emmerling and Tavoni (2017) use a different integrated assessment model, WITCH, with SGE, and they model uncertainty in both SGE and climate sensitivity. However, just like in Moreno-Cruz and Keith (2013), their characterization of uncertainty is a simple binary probability outcome. Our solution method allows us to fully characterize uncertainty over both SGE damages and climate sensitivity by including it in the planner's expectations, rather than merely conducting Monte Carlo simulations across various parameter values. We can impose any distribution of beliefs, e.g. lognormal, rather than binary probabilities. We model epistemic uncertainty over climate parameters and also over SGE parameters.[6]

In addition to our focus on uncertainty, our study provides two additional contributions to the literature. First, we focus on how the inclusion of SGE affects optimal abatement and the optimal carbon tax. Since SGE appears to be much cheaper than abatement, it is possible that including SGE will drastically reduce the price of carbon. If SGE means that the optimal carbon price is lower than current estimates of the social cost of carbon, this has very important policy implications. We calculate the welfare loss of ignoring this fact. We also explore how different assumptions about various parameter values affect the time path of optimal policy.[7]

[1] Recent reviews cover these technologies in more detail. Please refer to Heutel et al. (2016a), National Research Council (2015), and Latham et al. (2014) and the associated special journal issue.

[2] Barrett (2008) explores the "incredible economics of geoengineering," by which he means the fact that SGE is (potentially) so much cheaper than emissions abatement that it could be undertaken by a single country. See also Ricke et al. (2013), Weitzman (2015), and Moreno-Cruz (2015).

[3] Jones et al. (2013) also investigate the effect of abrupt suspension of GE (a "termination effect"), using a simulation of 11 different climate models. Also see Ross and Matthews (2009).

[4] Klepper and Rickels (2012), (2014) and Heutel et al. (2016a) provide review articles on the economics of geoengineering.

[5] We also characterize these uncertainties in the Appendix in an analytical model and derive policy implications.

[6] Several papers, including Baker and Solak (2011), Kolstad (1996), and Kelly and Kolstad (1999), modify DICE to include uncertainty, but without SGE.

[7] Barrett (2014) considers four different options for the time path of SGE, and Keith (2013) recommends starting at a low level of SGE and gradually increasing its use, but neither uses an IAM to generate optimal policy. Likewise, Wigley (2006) notes that more intensive use of SGE can reduce the need for abatement but does not consider optimal SGE levels.

Our other contribution is that we explicitly distinguish between damages from carbon concentrations and damages from temperature. Unlike abatement, SGE reduces temperatures without reducing carbon concentrations, either atmospheric or oceanic. Both types of carbon stocks may lead to damages, even if temperatures are brought back to preindustrial levels. For instance, ocean acidification may deplete corals and fisheries, and atmospheric carbon may affect precipitation patterns. Other papers have mentioned this issue, but to our knowledge ours is the first to incorporate it into an analytical model or a numerical simulation of solar geoengineering policy.

In our baseline deterministic simulations, we find that allowing SGE lowers the optimal level of abatement by up to 8 percentage points and lowers the optimal price of carbon by up to 15%, relative to a scenario where SGE is not allowed. Without SGE, temperature eventually increases by more than 4 °C above preindustrial levels, whereas that increase is kept to below 3° with SGE. As a result, the welfare costs of not allowing SGE are large – up to 4% of GDP. These magnitudes are especially surprising because our base case calibration is very conservative, i.e. leaning against a substantial role for SGE.[8]

We next demonstrate the importance of uncertainty. In simulations where climate sensitivity – the increase in temperature from a doubling of carbon concentrations – is uncertain, optimal policy includes more of both abatement and SGE, relative to the deterministic case. In simulations where there is uncertainty over the magnitude of damages from SGE, there is substantially less SGE than in the deterministic case, and the difference in optimal abatement is negligible. This reflects the risk aversion of the planner. When there is uncertainty over climate sensitivity and mistaken beliefs, then the welfare costs of ignoring SGE are twice as high as in the deterministic case.

Sensitivity analyses show that optimal abatement levels are less sensitive to parameter values than are optimal SGE levels. The degree to which damages from climate change arise from carbon directly, rather than from temperature, substantially affects optimal SGE deployment; if a high fraction of damages are from carbon, then SGE is used less intensively while more abatement is required. From sensitivity analysis on the discount rate we find that solar geoengineering works through a "buying-time" effect, allowing the planner to postpone costly abatement to a future time. This demonstrates that a main advantage of SGE over abatement is its quickness – SGE allows the planner to target short-run and medium-run temperature increases, while abatement can only affect the temperature with a long delay.

Finally, we further examine the buying-time effect by conducting simulations in which SGE is delayed for a given number of years. In these simulations, once SGE is allowed, it quickly increases and quickly brings temperature down to its optimal level. Abatement quickly falls as SGE is implemented and then increases at a lower rate than before SGE was allowed. Moreover, solar geoengineering is often thought of as an "insurance" against harsh or abrupt climate damages – as something that should be figuratively kept behind glass only to be broken in case of emergency. Our simulations where SGE is delayed for several years are one way in which SGE can be modeled as an "insurance" against climate risk.[9]

The next section of the paper provides motivating intuition for our analysis of SGE. Then, the following section briefly describes how we include SGE in the DICE model; details are in the Appendix. *We then* present our simulation results.

Conceptual framework

Here we briefly discuss the intuition underlying the numerical simulation model and results. A simple static analytical model of optimal policy in the presence of both abatement and solar geoengineering is presented in the Appendix.

Consider the decision of the optimal level of abatement (reducing GHG emissions). The optimal level is where its marginal costs are equal to its marginal benefits, where benefits are the reduced climate damages. This is demonstrated in the left-side graph in Fig. 1, which plots marginal costs and benefits of abatement (abatement is labeled a). The blue marginal benefit curve (labeled $MB|\text{No}-\text{SGE}$) indicates the marginal benefits from abatement conditional on there being no solar geoengineering used (i.e., $g = 0$). This constrained case represents the optimal policy prescription from a model that does not include or allow for SGE (e.g. DICE). Under this constraint, the optimal level of abatement is $a^{\text{No}-\text{SGE}}$ and the optimal emissions tax that would induce optimal abatement is $\tau \mid \text{No} - \text{SGE}$.

Consider next the optimal decision between abatement (reducing GHG emissions) and solar geoengineering (reducing the damages caused by GHG emissions by increasing Earth's albedo, or some other way). When solar geoengineering is allowed, ($g > 0$), the marginal benefit curve from abatement is lower than it is in the case where solar geoengineering is not allowed ($g = 0$). This is because each unit of pollution causes less damages, since the damages are reduced by solar geoengineering. This is demonstrated by the downward shift of the marginal benefit curve from the blue to the red curve.[10] The optimal level of abatement is lower when solar geoengineering is allowed than it is when geoengineering is not allowed ($a^{SGE} < a^{\text{No}-\text{SGE}}$), and the optimal emissions tax is lower ($\tau|\text{SGE} < \tau|\text{No} - \text{SGE}$). If solar geoengineering is available but ignored

[8] Specifically, we assign a very high value for the damages of SGE, on the order of magnitude of damages from climate change itself.

[9] We focus on SGE, which is just one type of geoengineering. A report by the National Research Council (2015) differentiates between two broad categories of geoengineering: albedo modification (which includes SGE) and carbon dioxide removal (CDR). We do not explicitly model adaptation, which is a third alternative (along with abatement and geoengineering) for dealing with climate change (Aldy, 2015). The costs of climate damages in our model can be interpreted as being net of adaptation; we leave it to future work to separately model adaptation from geoengineering.

[10] Proofs of this and all other claims in this section are provided in the analytical model in the Appendix.

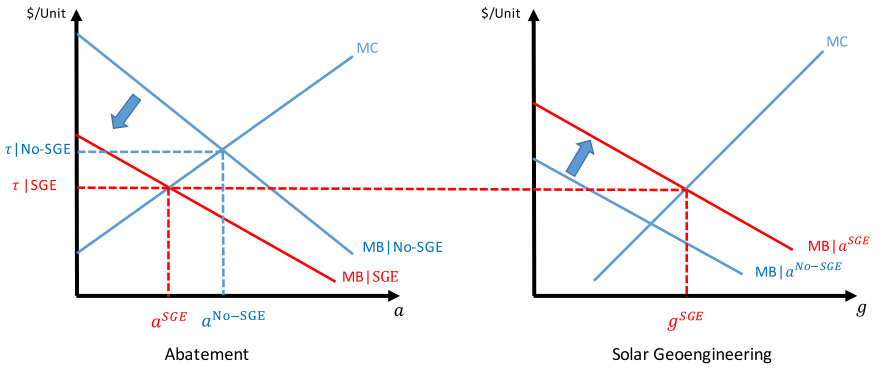

Fig. 1. Conceptual framework. In blue is the No-SGE case and in red the SGE case. The left-hand side presents the market for abatement, while the right-hand side shows the market for SGE.

in optimal policy models, then deadweight loss is created in the market for abatement.

The right-hand graph in Fig. 1 displays optimal SGE. As more SGE is used, the marginal benefit curve of abatement decreases, reducing optimal abatement. Furthermore, as less abatement is used, the marginal benefit curve of solar geoengineering increases (since there is more pollution, each unit of geoengineering is more beneficial). This is shown by the move from the blue MB curve to the red MB curve on the right-hand graph. The optimal level of both abatement and solar geoengineering occur when abatement's MB curve has decreased just enough and solar geoengineering's MB curve has increased just enough so that the marginal benefit of an additional unit is equal across both policies (indicated by the horizontal dotted line spanning the two graphs).

This simple graphical intuition underlies the economics behind our numerical simulations. We compare the DICE model without solar geoengineering (No-SGE) to our modification of DICE with solar geoengineering (SGE), and we demonstrate that optimal abatement is lower, the optimal carbon price is lower, and total costs are reduced (deadweight loss is eliminated) when SGE is allowed as a policy option.

This simple intuition ignores several important factors. First, there are two important sources of uncertainty: climate sensitivity and solar geoengineering damages. Second, solar geoengineering addresses some of the damages but not all. Given that our focus is on the numerical dynamic version of the model, we relegate the analytical treatment of uncertainty and differential damages to the Appendix and proceed with our numerical simulations using an integrated assessment model.

Dynamic simulation model

The dynamic integrated climate-economy (DICE) model by William Nordhaus is an IAM designed to find the optimal GHG abatement policy and calculate the social cost of carbon. It includes a representative-agent economic model with an endogenous capital stock and an exogenous level of technological growth. Carbon emissions are a byproduct of production but can be reduced through expenditure on abatement. The climate component of the model includes several equations describing the dynamic interaction between carbon concentrations in several layers: the atmosphere and upper and lower oceans. The atmospheric carbon concentration affects the atmosphere's radiative forcing. The human-caused change in radiative forcing is ultimately what affects atmospheric temperatures. Finally, the climate and economy sections of the model are integrated together since increases in temperature cause reductions in total economic output. A time period in the 2013 version of the model is five years, and the model is typically run over several dozen periods (hundreds of years). The DICE model and its results have been refined over the years, and summaries of the model's equations and results are available in Nordhaus (2014) as well as Nordhaus's personal webpage.[11] Our baseline calibration uses the 2013R version of the model.

Modifications to DICE

In this section, we present only the equations that we have modified from the DICE model to incorporate SGE. More details are available in the Appendix, including all of the equations of the model and how we calibrated it. We have modified DICE in the following five ways. First, while the only policy variable in the original DICE model is carbon abatement,[12] we add a second choice variable that reflects the intensity of solar geoengineering. Abatement intensity a_t can take values

[11] http://www.econ.yale.edu/~nordhaus/homepage/.

[12] The savings rate is another decision variable in the DICE model. However, in our simulations it is fixed at 25.8% in all periods. We find that whether or not savings is treated as a decision variable has no impact on the main results about optimal abatement and SGE policy.

between zero and one: when $a_t = 0$, there is no abatement, and $a_t = 1$ means all carbon emissions at time t are abated (zero emissions). Thus, a_t represents a *share* rather than a *level*. For symmetry, the choice variable for the intensity of SGE, g_t, is also modeled as a share rather than a level. When g_t equals zero, this represents no SGE. When $g_t = 1$, this represents "full" SGE, i.e. fully offsetting the warming effects from increased carbon concentrations at time t. However, unlike abatement intensity a_t, SGE intensity g_t could take a value larger than 1, representing more than fully offsetting temperature increases from climate change.

Second, there is a cost $G(g_t)$ of implementing solar geoengineering, analogous to the cost of abatement:

$$G(g_t) = G_{cost} \times \theta_1^g \times g_t^{\theta_2^g}. \tag{1}$$

This cost, expressed as a fraction of gross output that is lost to SGE implementation, is a quadratic ($\theta_2^g = 2$) function of SGE intensity g_t. To completely offset global warming ($g_t = 1$) costs 0.27% of global GDP in our base case, based on results in Crutzen (2006), McClellan et al. (2012), and Rasch et al. (2008); the details of this calibration are in the Appendix. The coefficient G_{cost} is a scale parameter representing the overall costs of solar geoengineering, and we vary this in the sensitivity analysis around its baseline value of 1. Other parameter calibrations are described in the Appendix.

Third, we add damages $\Omega_{SGE}(g_t)$ from solar geoengineering, analogous to the original model's specification of damages from climate change. For instance, sulfates are expected to exacerbate ozone depletion (Heckendorn et al., 2009). Precipitation could be drastically reduced (Ferraro et al., 2014, Robock et al., 2008). The sulfates injected into the stratosphere may condense and fall back to the atmosphere, contributing to acid rain[13]. These damages are expressed as a fraction of gross output that is lost, and they are a quadratic function of SGE intensity g_t:

$$\Omega_{SGE}(g_t) = \nu_G \times g_t^2. \tag{2}$$

These proportional damages are defined analogously to the way that DICE defines damages from temperature increases. The parameter ν_G is calibrated as described in the Appendix, and we consider different values in sensitivity analyses. We are very conservative (i.e. biased *against* SGE) in our base-case calibration: the amount of SGE required to completely offset the warming effects of CO_2 ($g_t = 1$) leads to damages of 3% of gross global GDP, which is about equal to damages from climate change itself under moderate warming.

Fourth, the benefits of solar geoengineering are modeled as directly modifying the radiative forcing equation. Radiative forcing is the difference between the amount of solar heat energy absorbed by the Earth and the amount radiated into space. When radiative forcing, F_t, is zero, the climate is in equilibrium and there is no warming effect. In the DICE model, the radiative forcing equation is

$$F_t = \eta\left(\log_2\left[\frac{M_t^{at}}{M_{eq.}^{at}}\right]\right) + Fex_t. \tag{3}$$

It is a function of the ratio of the current atmospheric carbon stock (M_t^{at}) to the preindustrial equilibrium atmospheric carbon stock ($M_{eq.}^{at} = 588$ gigatons of carbon (GtC), equivalent to about 277 ppm (ppm) CO_2) and exogenous forcing Fex_t due to anthropogenic emissions of GHGs other than CO_2 (assumed exogenous in DICE). The calibrated radiative forcing parameter is η. Atmospheric temperature T_t^{at} is affected by radiative forcing through the following equation:

$$T_t^{at} = T_{t-1}^{at} + \xi_1\left(F_t - \xi_2 T_{t-1}^{at} - \xi_3\left(T_{t-1}^{at} - T_{t-1}^{lo}\right)\right). \tag{4}$$

Current temperature depends on lagged atmospheric temperature (T_{t-1}^{at}), on radiative forcing F_t, and on lagged lower ocean temperature T_{t-1}^{lo}. A higher value of radiative forcing F_t (which is caused by higher atmospheric carbon M_t^{at}) leads to higher atmospheric temperatures T_t^{at}, all else equal. We modify the radiative forcing equation to incorporate solar geoengineering:

$$F_t = \left\{\eta\left(\log_2\left[\frac{M_t^{at}}{M_{eq.}^{at}}\right]\right) + Fex_t\right\} \times \left(1 - G_{eff} \times g_t\right). \tag{5}$$

The variable g_t is the amount of solar geoengineering in period t, and G_{eff} is a positive parameter that captures the effectiveness of solar geoengineering. Higher G_{eff} means less solar geoengineering needs to be implemented to achieve a given level of radiative forcing reduction. At a value of 1, radiative forcing F_t is reduced to zero (regardless of the carbon stock), completely compensating for the difference between incoming and outgoing radiation due to the increase in carbon stock. When $g_t > 1$, radiative forcing is negative, and global temperatures will reduce faster than they would even with no

[13] Though Kravitz et al. (2009) find that this effect will be insubstantial.

anthropogenic GHGs in the atmosphere. This implies that SGE can reduce temperatures much more quickly than abatement can. In particular, the effects of SGE on temperature occur in the same period in which SGE is implemented.

Fifth and finally, we decompose the damages from climate change Ω_{CC} so that they depend directly on temperature and also on atmospheric and ocean carbon concentrations. In the original DICE model, climate change damages (as a proportion of gross output) are a function only of atmospheric temperature T_t^{at} :

$$\Omega_{CC}\left(T_t^{at}\right) = \psi_1\left(T_t^{at}\right)^2 \tag{6}$$

By contrast, in our model these damages are also a function of atmospheric and ocean carbon concentrations M_t^{at} and M_t^{up}:

$$\Omega_{CC}\left(T_t^{at}, M_t^{at}, M_t^{up}\right) = \psi_1\left(T_t^{at}\right)^2 + \psi_2\left(M_t^{at} - M_{eq.}^{at}\right)^2 + \psi_3\left(M_t^{up} - M_{eq.}^{up}\right)^2 \tag{7}$$

The coefficients ψ_1, ψ_2, ψ_3 are calibrated so that the total climate change damages are identical across specifications from Eqs. (6) and (7), but the distribution of that total across temperature and carbon concentrations is allowed to vary.[14] In the base case, we set 80% of climate change damages from temperature increase, 10% from atmospheric carbon concentrations, and 10% from ocean carbon concentrations. By contrast, in the original DICE model and all of the previous studies that have modified DICE to include solar geoengineering, 100% of climate change damages are from temperature.

Appendix A.II provides more details of the calibration and includes all of the equations of the model, and it defines the planner's optimization problem. As described in the Appendix, much of the calibration must be somewhat arbitrary, since there is so little known about the costs and benefits of SGE. For instance, our coefficient representing the damages associated with SGE, ν_G, is calibrated based on previous studies, but the parameters used in those studies were essentially arbitrary. Thus, in our baseline simulations we set this parameter at a high level, to be conservative about our use of SGE (i.e. biased against using SGE). We also consider uncertainty in this parameter and conduct sensitivity analysis.

Other studies have also modified DICE to include solar geoengineering, and Table 1 compares our modifications to these other papers'. All of the papers allow SGE to directly modify the radiative forcing equation; our paper is the only one to allow SGE to enter as a multiplicative factor rather than a linear additive term. We choose a multiplicative factor for ease of interpretation: the policy variable represents the fraction of total anthropogenic forcing that is eliminated via SGE. We demonstrate later in the paper that this modeling choice has no substantive effect on the results. The next column notes that all of the previous studies except one allow for damages from SGE (apart from their implementation costs). We, like Gramstad and Tjøtta (2010), allow for these damages to be a quadratic function of SGE intensity and to be a multiplier on gross output; in this way they are modeled analogously to damages from climate change. Next, only this paper and Goes et al. (2011) and Bickel and Agrawal (2013) modify DICE's damages from climate change function. The other two papers allow for damages to be a function both of temperature and of the rate of temperature change, based on the fact that SGE can lead to rapid temperature changes (Matthews and Caldeiram, 2007). Their damage function is taken from Lempert et al. (2000). We are more direct in that we allow for damages to be a function of more than just temperature; this innovation is unique to this paper. And, as described earlier, our paper offers the most thorough treatment of uncertainty.

Solution algorithm

We use a state-of-the-art simulation algorithm, which can incorporate uncertainty, developed in Shayegh and Thomas (2015). This method is an alternative to the more standard method of value function iteration. In the standard value function approximation techniques, a set of features (a basis) is extracted at each state, and the value of the future states is approximated, often using a polynomial function of the basis. Here, we use a different approach. Instead of extracting features and building a polynomial function, we use an estimate of a weighted sum of the expected utility of several future states to approximate the future value function. Our method is computationally much faster than conventional methods, and it allows for a direct method of incorporating uncertainty when deriving optimal policy. More details of our solution method, including a comparison between its properties and that of the conventional method, are available in Appendix A.III.

The algorithm is uniquely suited to deal with uncertainty. We can model epistemic uncertainty over any arbitrary parameter or set of parameters. For example, we consider epistemic uncertainty over climate sensitivity, which is the equilibrium change in temperature due to a doubling of atmospheric carbon concentration. We assume that this parameter has a single true value, but the planner does not know this value with certainty. Instead, the planner has a belief characterized by a probability distribution over a set of values. This is incorporated into the solution method in the following way. In each period, for each possible action, the expected utility for future periods is calculated based on the distribution of parameter beliefs.[15] These future expected utilities are used in the value function approximation. At any period, the value function approximation is a weighted sum of the expected

[14] As in DICE, T_t^{at} is defined as the difference in temperature between the preindustrial equilibrium while M_t^{at} and M_t^{up} are defined as absolute levels. Thus, in Eq. (7), damages are a quadratic function of the differences in these three values between their respective preindustrial equilibrium levels.

[15] For example, for a given level of pollution abatement and geoengineering, the value of future utility depends on the value of climate sensitivity, since climate sensitivity affects how pollution changes utility. Expected utility is calculated by drawing a finite number of possible parameter values from the distribution and calculating the utility under each value, then averaging.

Table 1
Summary of modifications to DICE.

	Radiative forcing	Damages from SGE	Climate change damages	Uncertainty	Other modifications	Outcomes
Bickel and Lane (2009)	Linear term in forcing equation	None	No Modifications	None	Also model carbon capture geoengineering	Cost-benefit analysis for fixed levels of SGE; carbon price
Gramstad and Tjøtta (2010)	Linear term in forcing equation	Quadratic multiplier on gross output	No Modifications	None	None	Cost-benefit analysis for fixed levels of SGE
Goes et al. (2011) and Bickel and Agrawal (2013)	Linear term in forcing equation	Linear function of aerosols deployed	Damages a function of temperature and rate of temperature change	Monte Carlo	Alter discounting formula; change climate model to DOE-CLIM; intermittency in GE	Cost-benefit analysis for fixed levels of SGE and for optimal SGE/abatement mix; Bickel and Agrawal (2013) considers sensitivity analysis of Goes et al. (2011)
This paper	Multiplicative factor in forcing equation	Quadratic multiplier on gross output	Damages a function of temperature, atmospheric carbon, and ocean carbon	Epistemic uncertainty in climate sensitivity and SGE damages		Optimal levels of SGE and abatement; carbon price; sensitivity analyses

Note: This table compares several modeling choices among papers that modify DICE to include SGE, including this paper (bottom row).

utilities for four future periods.[16] The planner chooses the action to maximize based on this approximation of the value function. Then, the actual evolution of the state variables is defined by the true but unknown value of the parameter. The planner never learns the true value of the parameter or changes the prior beliefs in any way.

This treatment of uncertainty is preferable to simply using sensitivity analysis or Monte Carlo simulations. With sensitivity analysis, the model being solved is deterministic, but it is solved for several different parameter values. Monte Carlo simulations essentially do the same thing – they solve the deterministic model for different parameter values, where those values are drawn probabilistically from a defined distribution. By contrast, our approach incorporates beliefs over probability distributions of uncertain parameters into the solution method.[17] In addition to modeling uncertainty this way, we also conduct sensitivity analysis over parameters for which a probability distribution of beliefs is unknown. More details on our treatment of uncertainty are in Appendix A.III. As mentioned earlier, none of the other papers that incorporate SGE into DICE model uncertainty to the extent that we do.

Results

Though the main contribution of our study is on uncertainty, we begin by analyzing the deterministic case in order to understand the way SGE affects optimal climate policy. Then, we model uncertainty over two parameters: climate sensitivity and SGE damages. We next consider sensitivity analyses over several other parameter values, including the decomposition of climate damages between temperature and carbon, SGE costs and effectiveness, and the discount rate. Then we consider a constrained or non-optimal deployment of SGE in which SGE can only be used after a certain year. Finally, we consider an alternate modeling specification for our treatment of SGE.

Baseline deterministic case

We compare the outcomes under two deterministic scenarios: one in which SGE is not allowed ("No-SGE") and one in which it is allowed and unconstrained ("SGE").[18] The results are presented in Fig. 2.[19] Each of the panels (a) through (e) presents a policy outcome both under the No-SGE scenario (solid line) and the SGE scenario (dotted line). Then, panel (f) shows the welfare cost of ignoring SGE by plotting the annual GDP difference between the SGE and No-SGE case.

Panel (a) shows how abatement is affected when solar geoengineering is introduced as a viable policy instrument. The introduction of solar geoengineering lowers the level of abatement and delays the time when we transition to a clean economy. By 2185, abatement is at 100% (no emissions) in the No-SGE scenario. But, when SGE is allowed, optimal abatement is just 94% by 2185. This difference in optimal policy represents the role that SGE can play in the short and medium-term to moderate temperature increases. The optimal SGE deployment for the SGE scenario, shown in Panel (b) of Fig. 2,[20] is a "ramping-up/ramping-down" policy, starting out at low levels and gradually increasing as the damages from climate change increase. But, as abatement reaches its maximum deployment, SGE is reduced and eventually reaches a very low level. Although SGE is allowed to take a value greater than 1, its maximum value is just about one-half (i.e. offsetting half of the increase in radiative forcing from carbon concentrations). This is because the benefits from SGE are traded off against the (substantial) damages it could introduce. Eventually (beyond the time frame presented in the figure), SGE use declines towards zero, since carbon concentrations are reduced. SGE is a substitute for abatement in the short- and medium-run, but eventually abatement takes over.

The next two panels show atmospheric carbon dioxide concentrations and temperature changes. Because of the lower level of abatement in SGE relative to No-SGE, carbon dioxide concentrations peak at a higher level and later in the presence of solar geoengineering. Carbon in the SGE scenario peaks at about 1850 GtC in year 2155, relative to the case of No SGE where the concentration peaks at 1780 GtC in year 2145.[21] However, although carbon concentrations are slightly higher when SGE is allowed, temperature is drastically lower. Without SGE, temperature peaks in 2180 at 4.72 °C above

[16] Four is an arbitrary number that was chosen to provide a good fit with the exact solution in the deterministic case. Shayegh and Thomas (2015) use two periods ahead; we find here that four periods provides a better match in our model that includes SGE as well as abatement.

[17] Our approach uses random sampling to calculate the expected future utilities, but its advantage over Monte Carlo simulation is that these random sampling results are used to develop optimal strategy rather than merely demonstrating a range of possible outcomes. The optimal strategy is then used to make a prediction for any new realization of the uncertain parameter. This is the key advantage of stochastic optimization techniques over conventional Monte Carlo simulation: in stochastic optimization (or "reinforcement learning" in computer science language) the agent updates its optimal decision in the face of uncertainty based on a large (finite) number of previous observations of random realizations of uncertain parameters and outcomes, but in Monte Carlo simulation, the collection of the agent's responses to realizations of the random variable form a probability distribution that defines the range of optimal policy. In either case, as in our model, the beliefs of the planner do not change over time, i.e., there is no learning about the true value of the parameter.

[18] Later, we will consider scenarios where SGE is allowed but constrained.

[19] Our simulations are run for 60 periods (300 years). In these figures, we only present the outcomes for the first 55 periods (2010 through 2280) for climate-related outcomes and drop the last 5 periods to avoid end-of-simulation results. The No-SGE case is almost identical to the DICE model, except for our assumption about the distribution of climate damages from temperature versus carbon concentrations.

[20] SGE deployment is of course zero for all periods in the No-SGE scenario.

[21] 1 ppm of CO_2 equals about 2.13 GtC, so the peak of 1780 GtC equals about 840 ppm CO_2. Because of the assumption of exogenous technological change affecting the energy intensity of the economy, even without any abatement, emissions would eventually fall and carbon concentrations peak. Abatement hastens and reduces this peak.

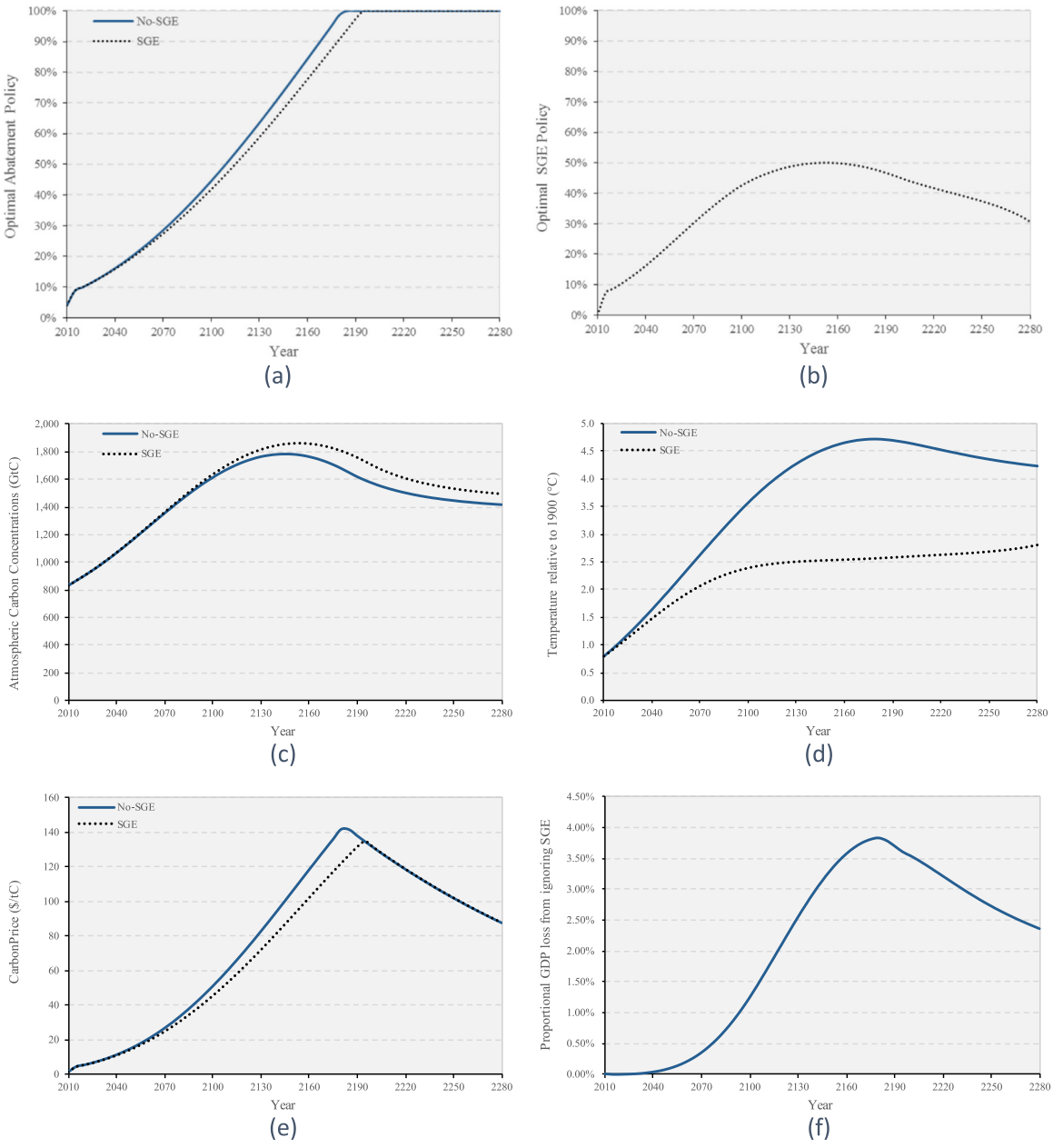

Fig. 2. Baseline deterministic simulations. In panels (a) through (e), the solid line shows the outcomes without SGE and the dotted line shows the outcomes with SGE. Panel (a) shows optimal abatement. Panel (b) shows optimal SGE. Panel (c) shows atmospheric carbon concentrations. Panel (d) shows temperatures changes relative to 1900. Panel (e) shows the carbon price associated with the optimal policy. Panel (f) shows the relative GDP loss due to ignoring SGE.

preindustrial, but with SGE the temperature increase in that year is just 2.57 degrees. With solar geoengineering, basically levels off around this temperature throughout the end of the simulation. This is the buying-time effect, often cited in the literature, where solar geoengineering keeps temperature below a deleterious level while the abatement technology improves enough to eliminate emissions (Keith 2013, Moreno-Cruz and Smulders 2007).

Panel (e) in Fig. 2 shows that the carbon price is lower when solar geoengineering is allowed. By 2180, the carbon price in the "No-SGE" scenario is more than $140 per ton, while it is about $120 per ton in the "SGE" scenario, a 15% decrease. The carbon price peaks once abatement reaches 100%, and it starts to decline as abatement productivity grows. This reinforces the intuition described earlier that ignoring solar geoengineering leads to an optimal carbon price that is too high.[22] This

[22] This carbon price equals marginal external damages along the optimal policy path as solved through DICE. In contrast, the term "social cost of carbon" often refers to marginal external damages along the baseline path, as a way of valuing reductions in carbon emissions. Aldy (2015) notes that this price (the social cost of carbon) can also be affected by the availability of geoengineering (and adaptation).

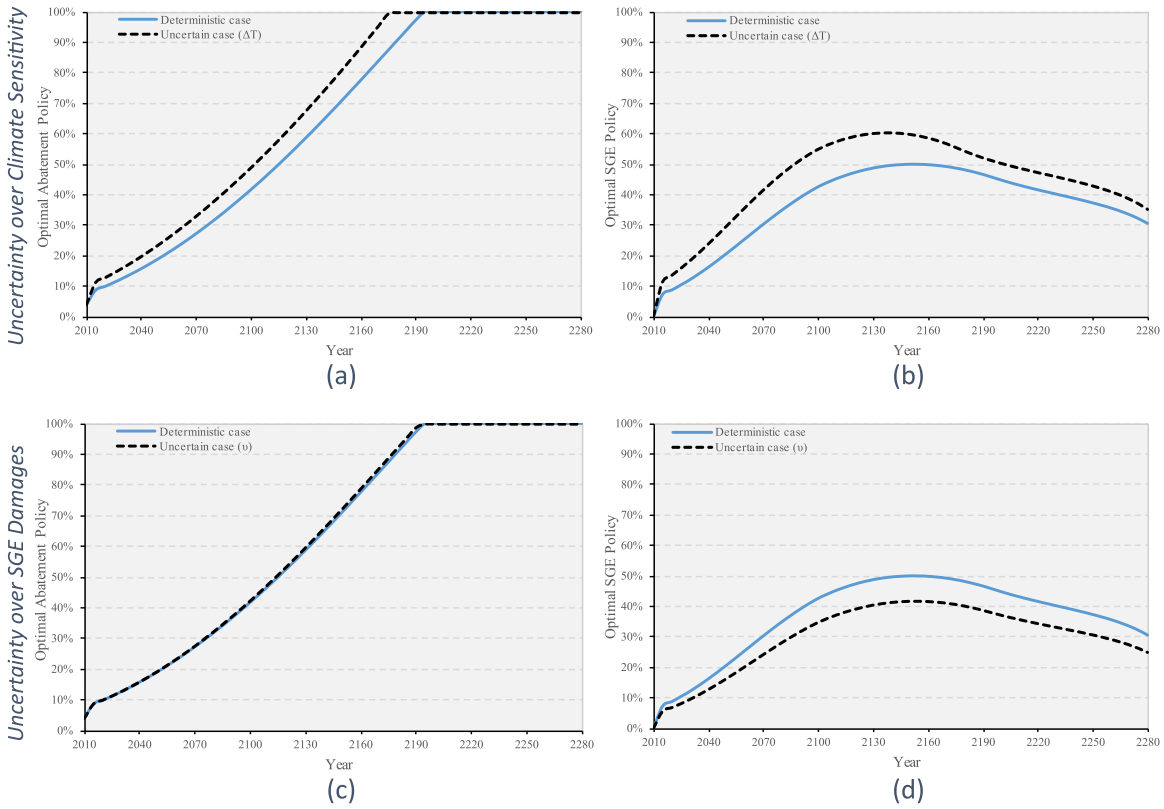

Fig. 3. Uncertainty simulations. The solid line shows the deterministic case, while the dotted line shows the simulation results under uncertainty. Panels (a) and (b) show optimal abatement and SGE policy, respectively, with uncertainty over climate sensitivity. Panels (c) and (d) show optimal abatement and SGE policy, respectively, with uncertainty over SGE damages.

change in the optimal carbon price and abatement intensity is especially surprising given the conservative assumption about the damages of SGE – even though SGE is very harmful itself, it still plays a major role as a substitute for abatement. By postponing costly abatement to future periods, SGE also helps to reduce the aggregate costs of climate change. This is shown in Panel (f) in Fig. 2 which plots for each year the proportional loss in net GDP of ignoring solar geoengineering.[23] For instance, in 2180, this value is 3.84%, indicating that net GDP is 3.84% lower in the "No SGE" simulation than it is in the "SGE" simulation.[24] This demonstrates the vast potential for SGE to reduce aggregate climate change costs – a savings of almost 4% of net GDP, even given the conservative assumptions about SGE damages, is remarkable.

These deterministic simulation results verify the intuition described earlier – allowing for solar geoengineering reduces the optimal level of abatement, reduces the optimal carbon price, and reduces total policy costs. These simulations are based on the baseline calibrated parameter values, which are subject to enormous uncertainties. Therefore, in the next section we incorporate these uncertainties into the solution method. Then, we conduct extensive sensitivity analyses over several parameter values.

Uncertainty

We consider uncertainty over two parameters: climate sensitivity, and the coefficient of SGE damages, ν_G.[25] In the real world there is uncertainty over many more parameters in the model (perhaps all of them) and over the model specification itself. We focus on the uncertainty in these two parameters because they are considered among the most fundamental sources of uncertainty, and this allows us to compare uncertainty in the climate system with uncertainty specific to SGE. For each source of uncertainty, we compare the solutions under uncertainty with the solutions in the deterministic case. Results are presented in Fig. 3. The top two panels (a and b) present optimal abatement and SGE, respectively, for the case of uncertainty over climate sensitivity. The bottom two panels (c and d) present them for the case of uncertainty over SGE damages. For each of the two simulated policy variables (abatement and solar geoengineering), we present the optimal path

[23] That is, $\frac{GDP_{SGE} - GDP_{NoSGE}}{GDP_{NoSGE}}$.

[24] This roughly corresponds to the area of deadweight loss from Fig. 1.

[25] This specification roughly corresponds to the two sources of uncertainty in the Appendix's analytical model.

for the deterministic case in solid blue curves (identical to the "SGE" results in Fig. 2), and the value from the uncertain case in dotted black curves. We present the other simulated outcomes (temperature, atmospheric carbon, the price of carbon, and welfare loss from ignoring SGE) in Appendix Fig. A2 and A3.[26]

First, consider uncertainty over equilibrium climate sensitivity. This parameter describes the equilibrium temperature change that results from a doubling of atmospheric carbon.[27] In our deterministic case this is set to 2.9 °C, which is also the mean value of the distribution in the case with uncertainty. The distribution over climate sensitivity takes the form of a truncated log-normal with a standard deviation of 0.7, calibrated based on the IPCC report (IPCC 2013). Panels (a) and (b) in Fig. 3 show that both abatement and SGE are higher under climate sensitivity uncertainty than under the deterministic case. Under uncertainty, by 2180 abatement has reached 100%, but in the deterministic case abatement is just 91% in this year. In that same year, SGE is 54% under uncertainty and 48% in the deterministic case. The fact that both abatement and SGE are higher in this case of uncertainty than in the deterministic case provides evidence of risk aversion – given the uncertainties, the planner is exercising precaution with the use of both policy tools.[28]

Although these simulations allow for uncertainty in climate sensitivity, they use a specific probability distribution of the uncertain parameter. In fact, this distribution itself is unknown, and many different estimated distributions arise from various models (see, for example, Fig. 1 in Millner et al., 2013). Thus, we re-run these simulations under alternative distributions for the uncertain climate sensitivity parameter, but with all other parameters kept at their base case values. The results, which are presented in Appendix Fig. A4, demonstrate that the optimal policy's qualitative behavior is largely invariant to the choice of distribution, though there is a large quantitative difference in outcomes. As the distribution becomes more dispersed (that is, as the variance parameter σ increases), or as the mean value (μ) increases, abatement increases, SGE increases and peaks earlier, and temperature remains lower when SGE is introduced.

Second, we allow the damages from SGE, measured by the parameter ν_G, to be uncertain. These damages represent the primary source of uncertainty over SGE.[29] The distribution of this parameter is assumed to be lognormal, with a mean value of 0.03 (representing a loss of 3% of output), identical to the value of the deterministic case, and a standard deviation equal to 1. Panels (c) and (d) in Fig. 3 present the results of these simulations. Here, SGE use is lower in the case of uncertainty than in the deterministic case (the solid curve vs. the dotted curve in panel d). By the year 2155 optimal SGE peaks at about 50% intensity in the deterministic case, while in this year SGE is just 42% in the uncertainty case. This difference represents risk aversion over the increased dispersion of risks from SGE damages. Panel (c) shows that abatement is higher in the uncertainty case than in the deterministic case, but only very slightly. Abatement reaches 100% in the same year in both cases (2190), and it is never more than 1.5 percentages points different across the two cases. Unlike with uncertainty over climate sensitivity in panels (a) and (b), uncertainty over SGE damages does not lead a risk-averse planner to substantially increase abatement; the slight increase in abatement is due to the substitution away from SGE.[30] As a result of the lower use of SGE under uncertainty, temperature increase is higher by about half a degree Celsius in the medium-run (Appendix Fig. A3, panel b).

The simulation results in Fig. 3 demonstrate the importance of incorporating uncertainty into models of optimal climate policy and SGE. Uncertainty can have substantial effects, either positive or negative depending on the source of uncertainty, on optimal SGE or optimal abatement.

We also consider simulations in which the beliefs of the social planner are substantively wrong. In Appendix Fig. A5, we present simulation results where the planner's beliefs over the values of climate sensitivity and SGE damages are characterized by the same distributions as in the simulations from Fig. 3, but the true value is two standard deviations higher than the mean of this belief distribution. In these simulations, like in the previous ones, the planner never learns the true value of the uncertain parameter or changes the belief distribution. The uncertain simulations are compared to the deterministic simulations where the true known parameter value is two standard deviations higher than in the base case. The top two panels show that under this case of mistaken beliefs about climate sensitivity, the use of both abatement and SGE is lower than it would have been if the planner had known its true value. The proportional GDP loss from ignoring SGE (not shown) in this scenario is 8 percentage points of GDP, about twice as high as in the base case of uncertainty. This demonstrates the fact that SGE is especially useful in this case of uncertainty and mistaken beliefs because it can reduce temperature much more quickly than can abatement. Panels (c) and (d) of Appendix Fig. A5 show that, by contrast, the differences in outcomes under mistaken beliefs about SGE damages are not much different than in the perfect information (deterministic) case.

[26] Even under the uncertainty case, there is still just one path for each outcome variable, rather than a distribution of paths. Although the planner's beliefs about the uncertain parameter take on a distribution, there is one true value of the parameter (which the planner never learns). The planner chooses a policy path without knowing the parameter value, so the planner's beliefs about future paths follow a distribution, but there is just one actual choice and one actual path for each outcome.

[27] In the DICE model and in our modification, this is actually a ratio of two deep parameters: $\frac{\eta}{\xi_2}$. We keep ξ_2 fixed at its baseline value and allow η to vary.

[28] This corresponds to our prediction from the theoretical model, described in Appendix A.I, that $\frac{\partial k_a}{\partial Var(\theta_X)}$ and $\frac{\partial k_g}{\partial Var(\theta_X)}$ can both be positive. A further demonstration of the risk aversion impact is the fact that the *ratio* of optimal abatement in the uncertainty case relative to the deterministic case is higher when SGE is not allowed than it is when SGE is allowed.

[29] National Research Council (2015).

[30] The theoretical model was ambiguous about both of these comparisons (see Eqs. (A6) and (A7) in the appendix).

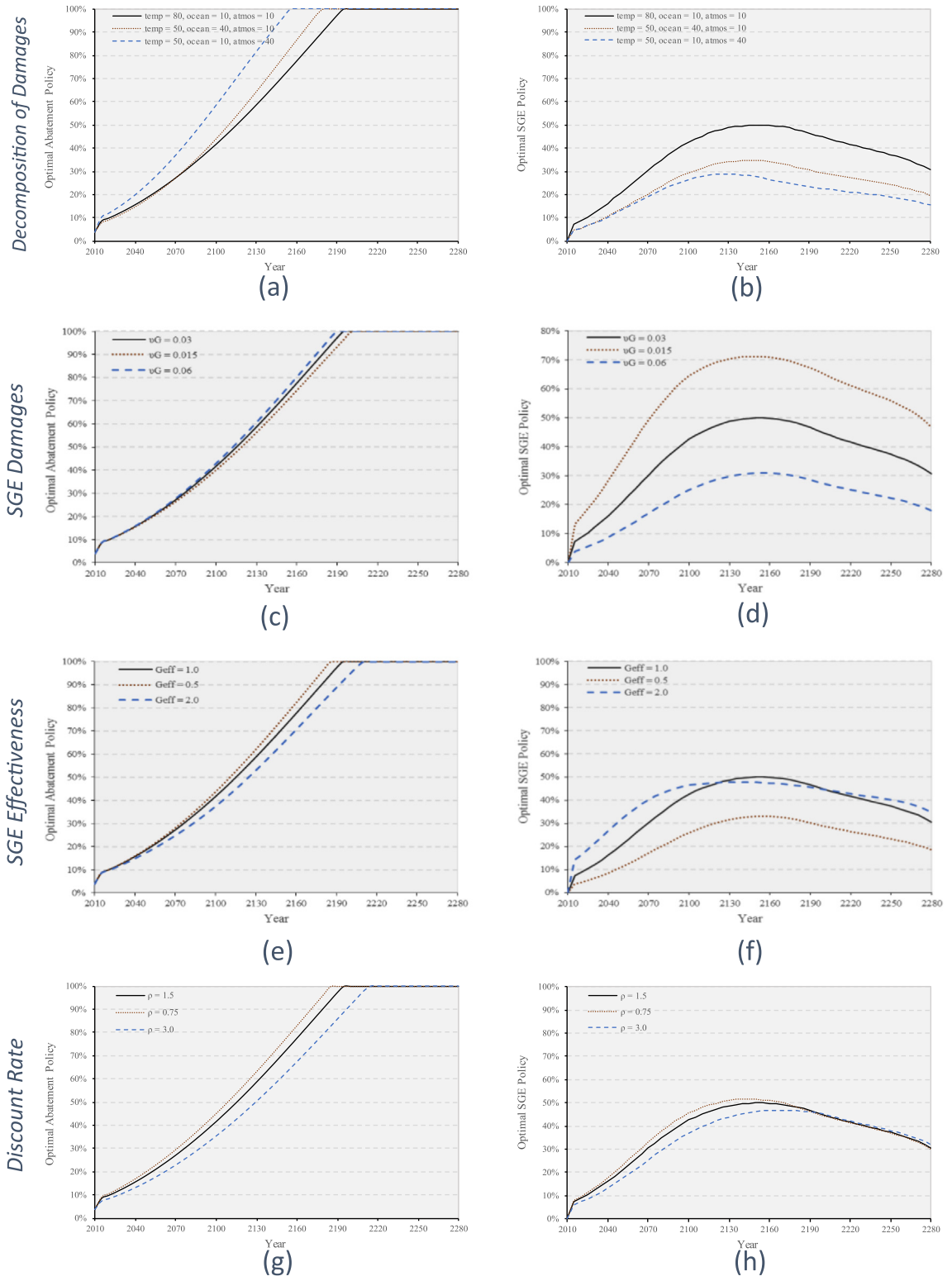

Fig. 4. Sensitivity analysis. Each row varies one parameter value and keeps all other parameter values at their baseline levels. The left column shows optimal abatement policy, and the right column shows optimal SGE policy. Panels (a) and (b) vary the decomposition of climate change damages between temperature, atmospheric carbon, and ocean carbon. Panels (c) and (d) vary SGE damages. Panels (e) and (f) vary SGE effectiveness. Panels (g) and (h) vary the social discount rate.

Sensitivity analysis

Next, we return to the deterministic specification of the model and conduct sensitivity analyses by solving the model under different parameter values. For all of the parameters associated with SGE, there is very little in the scientific literature to draw on and calibrate the base case parameter values. Therefore, both the base case parameter values and the values taken in the following sensitivity analyses are somewhat arbitrary. As we said before, the point of this paper is not to provide precise quantitative policy recommendations, but rather to explore the impact of the modeling assumptions on optimal policy. The purpose of these sensitivity analyses is thus to provide a way to understand where research is needed the most in order to reduce uncertainty on the possible outcomes of SGE.

Fig. 4 summarizes the results. Due to space considerations, in Fig. 4 we only show how changes in parameter values affect optimal abatement (in the left-hand column) and SGE policy (in the right-hand column). Other climate and economic outcomes of these simulations (temperature, atmospheric carbon, the price of carbon, and welfare loss from ignoring SGE) are shown in Appendix Figs. A6–A9. Each row of Fig. 4 represents a sensitivity analysis over one parameter value, as described below. The solid line represents the baseline parameterization, while the dotted lines represent alternative parameter values.

Composition of damages

A unique contribution of our study relative to others is that we explicitly model damages from carbon concentrations separately from damages from temperature increases. Because SGE reduces temperatures without reducing atmospheric or ocean carbon concentrations, it cannot completely offset all damages from climate change. In the baseline specification, we assume that 80% of climate damages are directly from temperature, 10% are from atmospheric carbon concentrations, and 10% are from ocean carbon concentrations (see the Appendix for details). Admittedly, this calibration is arbitrary; it is unknown just how much of climate damages come from each of these sources. Therefore, in Panels (a) and (b) in Fig. 4, we present simulation results where we vary this decomposition of climate damages. In addition to the baseline case, we simulate two other damage decompositions, in each of which damages from temperature only account for 50% of climate damages. The remaining 50% of damages are split between atmospheric and ocean carbon, either 40% from oceans, 10% from atmospheric, or vice versa. The solid black curves in Fig. 4 represent the baseline scenarios where 80% of climate damages occur from temperatures, and the two dotted curves represent the alternative assumptions on the composition of damages.

Abatement is higher when atmospheric carbon accounts for a higher fraction of damages (Panel a), although the difference between the baseline abatement and abatement when ocean carbon accounts for a higher fraction of damages is small. Comparing the baseline case to either of the two alternate decompositions shows that there is more solar geoengineering when temperature accounts for a higher fraction of climate damages (Panel b). SGE is less effective relative to abatement when temperature accounts for less damages, and so less of it is deployed. When temperature accounts for 80% of total damages, SGE intensity peaks at 50% intensity. But, when temperature only accounts for 50% of total damages, SGE intensity peaks at just 35%. Comparing the two alternative decompositions to each other shows that there is slightly more solar geoengineering and substantially less abatement when ocean carbon concentrations account for a higher fraction of damages than do atmospheric carbon concentrations. Abatement more directly affects atmospheric rather than ocean carbon, since the absorption of emitted carbon by the ocean is gradual and slow. If atmospheric carbon is more damaging than ocean carbon, more abatement and less SGE are needed.[31]

The actual decomposition of damages into damages from ocean carbon, atmospheric carbon, and temperature is unknown. In fact, atmospheric carbon may yield benefits from increased agricultural productivity. For policy that only includes abatement, the distinction is unimportant. But because SGE severs the direct link between carbon and temperature, the distinction matters.

SGE damages

The next parameter that we vary is the coefficient on damages from SGE, ν_G. In the previous section, this was one of the parameters that we treated with epistemic uncertainty. Here, we solve the deterministic model but under three different parameter values. Panel (d) of Fig. 4 shows that variation in the damages from SGE causes a very wide range of optimal SGE deployment. In the base case ν_G is calibrated to 0.03. When damages are half as large as the base case ($\nu_G = 0.015$), SGE eventually reaches 70% intensity. When damages are twice as high as the base case ($\nu_G = 0.06$), then SGE peaks at only 30% intensity. However, panel (c) demonstrates that the variation in optimal abatement is much smaller than the variation in SGE. When SGE damages are doubled and SGE deployment falls by almost half, abatement increases only slightly. This is analogous to what we demonstrated in panels (c) and (d) of Fig. 3 – uncertainty in SGE damages has a much larger effect on optimal SGE than on optimal abatement. This exercise demonstrates that the magnitude of damages from SGE – a parameter over which very little is known – has an enormous effect on optimal SGE policy and temperature outcomes.

SGE effectiveness

The parameter G_{eff} represents the effectiveness of SGE. Its base case value is defined as one; when it is twice as high ($G_{eff} = 2$), then the same amount of SGE intensity will have twice as high an effect on radiative forcing (see equation above).

[31] This corresponds to the result from the Appendix's analytical model that $\frac{\partial k_a}{\partial \lambda_d} < 0$ and $\frac{\partial k_g}{\partial \lambda_d} > 0$.

Panels (e) and (f) of Fig. 4 show how SGE effectiveness affects its deployment and abatement – if SGE is more effective, it should be used more intensively, and abatement used less intensively. When SGE effectiveness is very low ($G_{eff} = 0.5$), it is used much less intensively, peaking at just 33% in 2155. When it is very effective ($G_{eff} = 2.0$), it is used very intensively in the short run, reaching 27% intensity by 2040, compared to just 16% at the base case value. However, in the medium run its use is slightly less than in the base case, in part because it being more effective means that less of it needs to be used to achieve the same temperature outcome. Appendix Fig. A8 shows that more effective SGE results in higher carbon concentrations but much lower temperatures. With a high effectiveness of $G_{eff} = 2$, temperatures are almost always kept under the current levels for the entire simulation. This demonstrates that while SGE effectiveness has a modest effect on optimal policy, it has an enormous effect on actual policy outcomes (temperatures).

Discount rate

Increasing the discount rate ρ (panels g and h of Fig. 4) decreases the amounts of both abatement and solar geoengineering. The explanation for the effect on abatement is clear – abatement involves a present cost in return for a future benefit. It is well-known that the choice of discount rate can have a profound effect on optimal abatement (Nordhaus, 2007). The effect on SGE is less clear, since SGE involves both costs and benefits in the present due to its immediate impact on temperature. However, SGE also has a lagged effect on temperature because of the inertia in the climate system.[32] Caring less about the future therefore implies being less willing to invest in both abatement and in SGE.

This exercise sheds light on one of the crucial roles of SGE – it is able to reduce temperatures in the short and medium run, though abatement can only affect temperature in the long run. To illustrate this buying-time effect, panel (f) of Appendix Fig. A9 plots the annual loss in GDP from ignoring SGE. In the base case it peaks at just under 4% of GDP, but it is higher (about 4.25%) under a higher discount rate. This is because with the higher discount rate, being able to postpone costly abatement until the future is even more valuable than it is with a lower discount rate.

Other parameters

In the Appendix, we also present sensitivity analyses over two other variables. The first represents the costs of SGE, G_{cost}, and these are presented in Appendix Fig. A10. As the implementation costs of SGE increase, less SGE is deployed. Because these costs are so low in the base case, a large change (doubled or halved) in the coefficient in front of these costs has only a small effect on SGE deployment or any other outcome.[33] Second, Appendix Fig. A11 shows sensitivity analyses over abatement cost, a parameter not directly related to SGE. But because SGE is a substitute for abatement, any change in the relative price of abatement affects optimal SGE deployment.[34]

Delaying SGE

As discussed earlier, SGE is often thought of as an "insurance" policy that should only be used as an emergency response to unprecedented climate change. For instance, policymakers may want to prohibit SGE until a certain year, or until global average temperature increases beyond 2 °C. While this restriction is not optimal in our model (assuming that all costs and benefits of SGE are captured in our model), it may be more politically viable.

We explore this issue in Fig. 5 by presenting simulations in which SGE is not deployed optimally in each period, but instead is subject to an exogenous delay, perhaps due to political restrictions. Once this certain year (the "trigger year") is passed, then SGE is again allowed to be used without constraint.[35] We consider several different trigger year values to gauge the impact of increased delay. Panel (a) shows abatement, and panel (b) shows the optimal SGE policy. After a delay, once SGE is allowed there is an immediate jump up in SGE intensity, which is greater than the SGE intensity would have been without the delay. After this initial jump, the system adjusts the optimal SGE use to bring temperature change down to what the optimal level would be if SGE were implemented in the first period of our simulation (Panel c). Panel (a) shows that abatement responds to the trigger year by immediately falling, and then increasing at a lower rate until it reaches its maximum level, slightly later.

Panel (d) shows the welfare loss due to delay, in terms of proportional loss of net GDP. That is, each curve in panel (d) compares net GDP under the delayed SGE scenario with net GDP under the unrestricted SGE scenario (the "SGE" curve in Fig. 2). We learn two things from this panel. First, the welfare loss is increasing with the delay. Under the 2040 trigger year, the GDP loss peaks at just 0.083%, while under the 2220 trigger year it peaks at 3.69%.[36] Second, once SGE is allowed, the net GDP losses come down relatively quickly. For example, under the 2160 trigger year scenario, welfare loss peaks at 4.06% right before SGE is allowed. But, after just five periods it drops to 1.4%. This speaks to one of the key advantages of SGE: its fast response and its ability to buy time. Panels (c) and (d) both demonstrate how quickly SGE can act to reduce

[32] Even though radiative forcing is not a state variable, atmospheric temperature is (Appendix Eq. (A23)).

[33] The level of SGE intensity in 2150 changes from just 47% for the expensive SGE scenario to 51% for the cheap SGE scenario.

[34] Appendix Fig. A11 shows sensitivity analysis over the value of the main parameter of the abatement cost function, θ_2. A larger θ_2 means cheaper abatement. Larger θ_2 yields a higher optimal level of abatement and a lower optimal level of SGE.

[35] An alternative scenario would be to assume that SGE is prohibited until a certain temperature is reached, rather than until a predetermined year. These results are qualitatively similar to those in Fig. 5.

[36] The 2280 trigger year scenario bans SGE for almost the entire simulation, and therefore the welfare loss for this scenario is almost identical to that shown in panel (f) of Fig. 2, comparing the SGE and No-SGE scenarios.

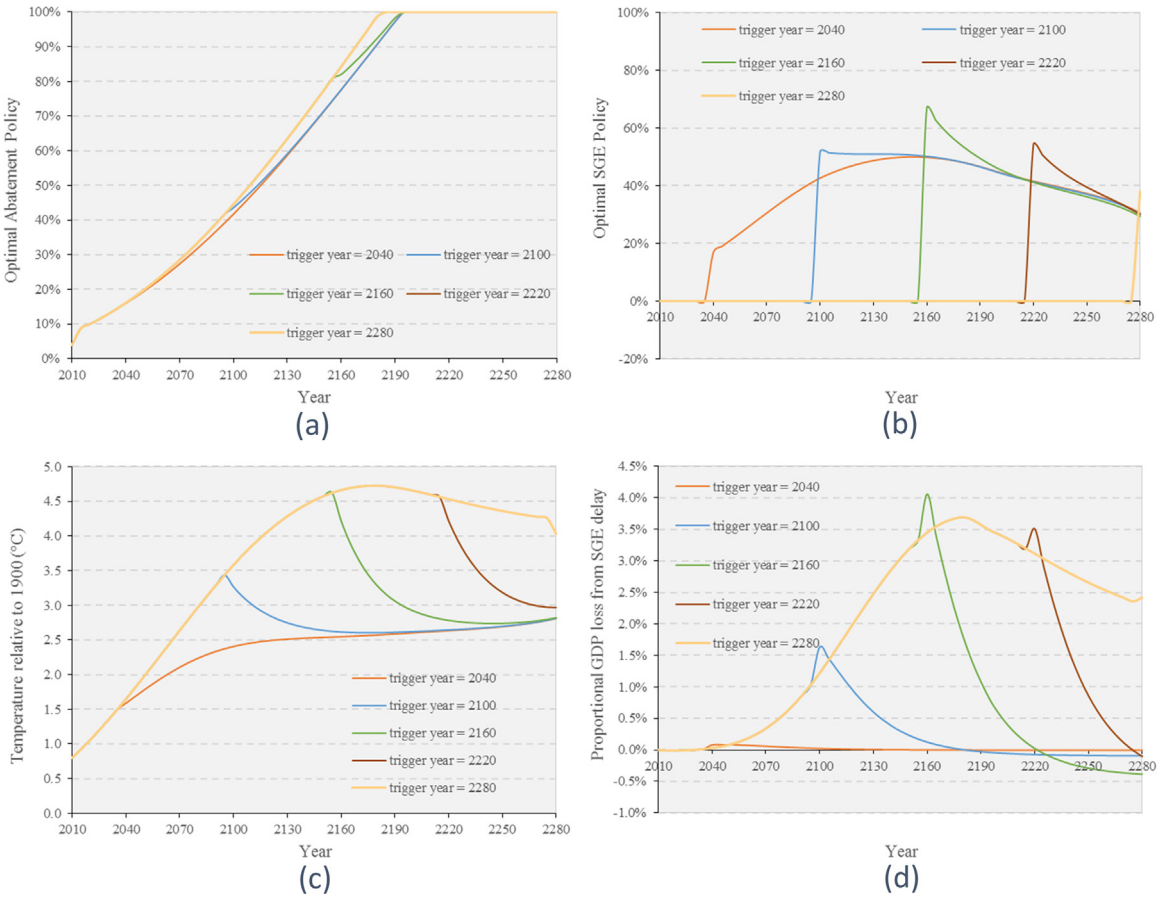

Fig. 5. Effects of delaying SGE. Each panel shows results for simulations under five different "trigger year" scenarios – a year before which SGE is banned. Panels (a) and (b) show optimal abatement and SGE policy, respectively. Panel (c) shows atmospheric temperature. Panel (d) shows the relative GDP loss due to the delay in deployment of SGE compare to the case without delay.

temperatures and therefore reduce welfare costs. This is the key reason for SGE's hump-shaped pattern in the unrestricted case – it is used in the short- and medium-run to buy time until abatement becomes more affordable. Furthermore, this also offers an argument for delaying the use of SGE until we learn more about its costs and damages, since the welfare loss from these delays can be quickly undone.

Alternative modeling of SGE

In this last subsection, we consider an alternative specification for how we introduce SGE into the DICE model. In our base specification we have chosen to model SGE as having a multiplicative effect on radiative forcing (Eq. (5)). The appeal of this specification is that the interpretation of SGE intensity mirrors that of abatement intensity – it is a fraction or share of total radiative forcing between zero and one that can be undone by SGE. However, as noted in Table 1, this modeling choice differs from that of other papers that have introduced SGE into IAMs. Those other papers model SGE as a linear term affecting radiative forcing. This can be represented by the following radiative forcing equation, in place of Eq. (5):

$$F_{t+1} = \left\{ \left[\eta\left(\log_2 M^{at}_{t+1} - M^{at}_{eq.} \right) \right] + Fex_{t+1} \right\} - G_{eff} \times g_{t+1} \tag{8}$$

Here the units of g_{t+1} are watts per square meter (W/m^2), and G_{eff} again is a coefficient representing SGE effectiveness, here set equal to one. Because of this different definition of g_{t+1} (it is now a level, in W/m^2, rather than a percentage intensity), several other model parameters must be recalibrated.[37] This alternative modeling implies that g_t is now a *level* rather than a

[37] In particular, the parameters of the cost function $G(g_t)$ and the damage function $\Omega_{SGE}(g_t)$ must be recalibrated, so that the costs and damages of a given level of SGE are comparable across the two modeling strategies. We conduct this calibration in the following way. We choose a reference year, 2150, which is the year in which radiative forcing F_t peaks in the No-SGE simulation shown in Fig. 2. The peak value is 6.67 W/m^2. We calibrate costs and benefits of SGE in this new specification such that costs and benefits for g_t = 100% (under the baseline specification) and g_t = 6.67 (under the new specification) are

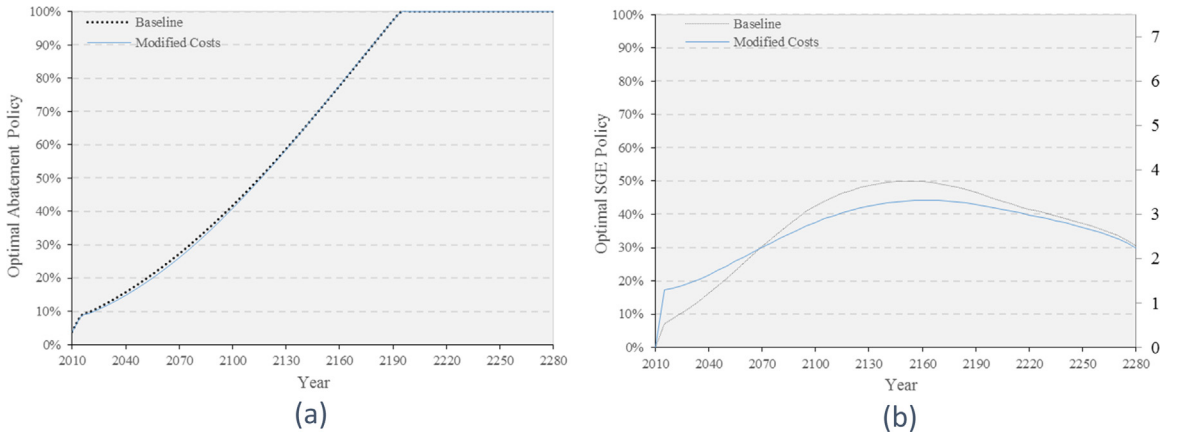

Fig. 6. Alternative modeling of SGE. This figure compares the baseline deterministic SGE simulation (dotted curve) with the simulation in which SGE is modeled as a linear effect rather than a multiplicative effect on forcing (solid curve). Panel (a) is optimal abatement; panel (b) is optimal SGE.

share, although we calibrate it so that g_t on average is still as effective as in the original model.

Panels (a) and (b) of Fig. 6 present the results for optimal abatement policy and optimal SGE policy under this alternative specification, along with the base case specification for comparison. In panel (b), the left y-axis measures SGE intensity in the baseline case (multiplicative, as a fraction of forcing reduced), while the right y-axis measures SGE in the linear case (in W/m^2). The remaining policy outcomes are presented in Appendix Fig. A12. The results under this specification are nearly identical to those in the base case. The only observable difference is in the shape of the optimal SGE path – there is more SGE upfront and slightly less SGE later under the linear specification than in the base case specification. This simulation demonstrates that this particular modeling assumption does not substantively affect any of the results presented above.

Conclusion

Solar geoengineering has the potential to create a paradigm shift in climate policy. It can lower the costs of dealing with climate change and reduce the need for abatement and a high carbon price. This study makes three crucial contributions. First, uncertainty over both the climate system and solar geoengineering damages can substantially affect optimal policy. Second, models that ignore solar geoengineering will prescribe policies that abate too much, cost too much, and result in a carbon price that is too high. Third, because solar geoengineering reduces temperatures but not carbon concentrations, it is merely an imperfect substitute for abatement.

We explore these issues using a modified version of DICE that incorporates SGE and uncertainty. In the baseline deterministic case, we find that allowing for SGE has a substantial impact on optimal policy. The optimal level of abatement is up to eight percentage points lower when allowing for solar geoengineering than when not allowing for it, and the optimal carbon price is up to 15% lower. Atmospheric carbon concentrations are higher when SGE is allowed, but temperature is kept more than two degrees Celsius lower. The welfare cost of not allowing SGE is as high as four percent of GDP. These results are very conservative, in that our base-case parameterization assigns very high damages to SGE and thus makes SGE a much less attractive option than it may actually be. Uncertainty has a large effect on optimal policy. Under uncertainty over climate sensitivity, both optimal abatement and optimal SGE act together to manage this risk, so their level is higher than in the deterministic case. This behavior represents aversion to climate risks. However, under uncertainty over SGE damages, optimal SGE is lower and abatement is slightly higher than in the deterministic case. That is, under this form of uncertainty, risk aversion takes the form of a reduction in the amount of SGE and an increase in abatement to compensate. Of course, results are sensitive to the parameter values, many of which are unknown. Still, under a wide range in parameter values, the optimal level of abatement does not vary substantially though the optimal level of SGE does. In particular, our results show that the optimal SGE is less sensitive to the cost of its deployment than to its effectiveness or potential damages. This highlights the need for prioritizing the research on the effectiveness and potential damages of SGE rather than its cost. As with all climate models, more precise parameter values are essential for pinning down specific policy recommendations. More research is needed to improve IAM models that include solar geoengineering.

We caution that these results should not be interpreted as a policy prescription for immediate deployment of solar geoengineering. The uncertainties surrounding the calibration of the model, in particular the damages associated with solar

(*footnote continued*)
equivalent across the two specifications. That is, $G(g_t = 100\%)$ from the original specification equals $G(g_t = 6.67 W/m^2)$ from the alternate specification, and likewise for the damage function Ω_{SGE}.

geoengineering, are too great to be able to do so. Instead, the main contribution of this paper is in its qualitative exploration of how including SGE in climate models affects the optimal deployment of abatement and the price of carbon, of how uncertainty affects optimal policy, and of how important it is that solar geoengineering reduces temperatures but not carbon concentrations.

Furthermore, IAMs like DICE have been criticized. Pindyck (2013) argues that they tell us "very little" and are "close to useless" because so many of the calibrated parameter values are ad hoc with little empirical foundation. This is demonstrated by the fact that the policy recommendations can be so sensitive to arbitrarily chosen parameter values, for instance the discount rate. Because our numerical analysis relies on DICE, it is subject to these criticisms. However, even if one accepts these critiques and is skeptical of IAMs, we argue that our analysis has merit. Though the point estimates of optimal policy paths should be interpreted with caution, how they vary with parameter values (i.e. the sensitivity analysis) still provides insight. Further, the simulations demonstrate that it is important to consider SGE in optimal policy design, with or without IAMs.

Still, the fundamental contribution made by this study has important policy implications. It is not efficient to merely estimate the marginal external damages of a ton of carbon and institute that carbon tax, if the external damages are estimated in a model without the possibility of solar geoengineering. Our results suggest that this may in fact be the case, and that for this reason the carbon price currently being used by policymakers may be too high.[38] Of course, there are many other potential reasons why the carbon price currently used may be too low – estimates may omit many benefits from carbon reductions.

Our research emphasizes the need for more information on costs and benefits of solar geoengineering. Extensions to our analysis may yield valuable policy lessons. Further research could expand the set of parameters modeled as uncertain variables, or add refinements to either the climate model in DICE or its treatment of economic costs or growth. Heutel et al. (2016b) consider how solar geoengineering can address the issue of tipping points, or irreversibility and discontinuities in climate damages. Endogenous learning about climate or SGE should be considered, for instance by adopting the Bayesian learning framework of Kelly and Kolstad (1999). This would allow for a calculation of the value of information about SGE, and the benefits of research and development or field experiments. Explicitly modeling how adaptation affects optimal abatement and solar geoengineering is a fruitful extension that could yield additional insights. Because the model is dynamic, it can be used to examine intergenerational justice. The model could be disaggregated by region – potentially important if the effects of SGE are not uniform across the globe.[39] One drawback of SGE that could be more thoroughly explored is that it is temporary – SGE has to be more or less continuously maintained or else temperature may increase very quickly. Finally, there are many issues related to SGE that we do not or cannot address using an IAM – including a fat-tailed distribution of risks, distributional effects, and ethical issues related to the question of abatement versus SGE.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at https://doi.org/10.1016/j.jeem.2017.11.002.

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[38] The SCC used by the EPA and other federal agencies is described here: http://www.epa.gov/climatechange/EPAactivities/economics/scc.html.

[39] The RICE model is a regionally disaggregated extension of the DICE model. Kravitz et al. (2014) studies the regional disparities arising from SGE deployment. Moreno-Cruz et al. (2012) account for regional inequalities in SRM effectiveness.

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